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AN ANALYSIS OF THE EFFECT OF ELIMINATION OF SIX BIG LOSSES ON INCREASING PROFITABILITY IN STEEL ROLLING MILL COMPANIES

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Original Article

ABSTRACT

Increasing productivity is very important for companies to achieve success in business processes. The concept of Total Productive Maintenance (TPM) has been used in various companies to increase productivity so that production performance becomes more efficient and results in sustainable company profitability performance. In Steel Rolling Mill Company is a capital intensive industry that is 80% of production costs are raw materials and energy, so the successful elimination of Six Big Losses is a key success factor to gain profitability. To analysis the effect of Six Big Losses elimination on productivity, decreasing production costs and increasing profitability is done by evaluating all Six Big Losses indicators through PLS-SEM, the data used are operating performance data of PT. XYZ during the period of 2015 - 2017. From this study revealed that the OEE variable is very significantly influenced by 2 (two) of the 3 (three) constituent indicators namely Availability and Performance, both of these indicators influence: Increased productivity, Decreased production costs and Increased profitability from the company. Priority improvements that must be made by considering competitor data (Benchmarking) are elimination: Breakdown losses (L1), Setup and Adjustment losses (L2), Idling and Minor Stoppages (L3), and Reduced speed (L4)

***KEYWORDS:** Six Big Losses, TPM, SEM-PLS, OEE & Profitability*

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INTRODUCTION

According to (Prasetyo, 2010) strength, the robustness of the iron and steel industry possessed by a country is one indicator that shows the strength and lack of economy of a country in the world at present and in the future. The current state of China is undoubtedly the condition of the strength and capability of its economic movements, where China is currently the world's largest producer of iron and steel. If European countries were the giants of the world economy in the early 18th century and America in the 20th century, then the world economic giant in the 21st century was China.

According to (Hasni, 2011) Indonesia's economic growth is strongly influenced by the national steel industry. Where the linkages of the national steel industry are very strong with other industries (backward and forward linkages), such as the machinery industry and the transportation industry and others. As shown, the increase in steel sector production can affect the demand for input-sector inputs of 1.2744 according to the results of backward linkage analysis. This means that every increase in steel sector output is IDR 1 will increase the demand for inputs from other sectors in the amount of IDR. 1.2744. The electricity and gas energy sector is the main input

for the steel sector production. While the results of the forward linkage analysis of the steel sector are 1.0203

According to (WorldSteel, 2016) in 2013 Indonesian steel consumption was 61.6 kg per capita. In order to become a developed country, Indonesia must have an annual per capita steel consumption of 500 kg. With annual per capita steel consumption levels still low, Indonesia still needs at least 120 million tons of steel production capacity to support the consumption of 500 kg per year per capita.

According to (Worldsteel, 2016) the national profile steel mill production capacity is 2.381 million tons while the national need is 1.023 million tons. With the Supply-Demand imbalance of steel products, the China-Asean free trade agreement (CAFTA) and investment plans for the construction of integrated steel mills by Chinese investors in Indonesia will force domestic steel production to improve and innovate the production process to produce quality products at a cost competitive and profitability

STUDI LITERATURE

Quality, Productivity & Profitability

Quality is defined as the ability of a product or service to fulfil the desires of its customers (P. Tampubolon, 2004). And according to (Heyzer. J., 2001), building quality is a way for a company to create profitability, as described in the following figure 1:

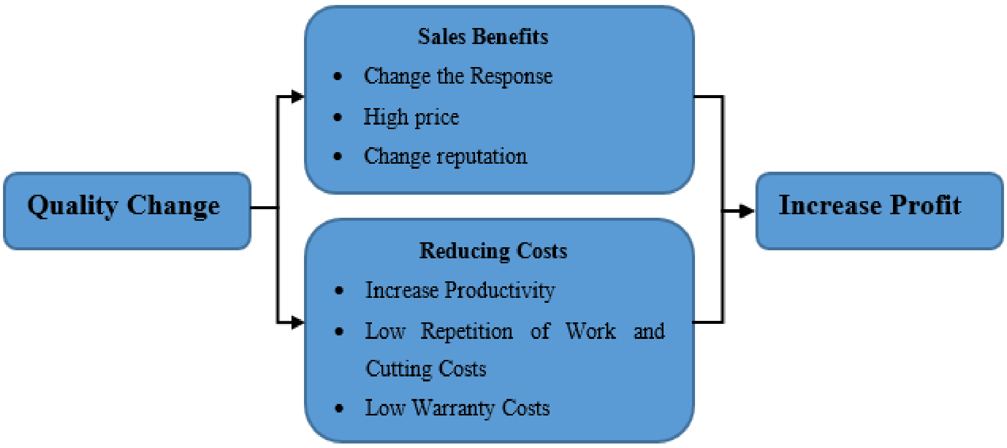

Figure 1: Quality Gives Way to Change Profitability

(Maletič, D., Maletič, M., Al-Najjar, B., & Gomišček, B., 2012)states that productivity is not the same as production, but production, quality performance, yield, are components of productivity efforts. Thus, productivity is a combination of effectiveness and efficiency

Company profitability is measured using the difference between the selling price and cost of goods sold (COGS). Profitability is the company's ability to generate profits in relation to sales (Singgih, 2006)

Cost Quality

Cost of Production is all costs incurred in the production process in producing a product until it is ready for sale. Cost of Production consists of the following fees:

Direct Material Costs

It is all costs to obtain raw materials to ready-made materials which include: Price of raw materials, transportation costs, storage and others.

Direct Labour Costs

Is part of the wages or salaries of all workers involved in making products, the order of certain jobs, or the provision of certain services.

Over Head (OH) Factory Costs

Defined as indirect raw materials, indirect labour and other factory costs that are not easily identified or charged directly to certain jobs, products, and final cost targets. OH costs, consider two characteristics, which are related to the specific relationship between OH costs and the product itself and the volume of production. Based on the relationship between OH and the volume of production, OH costs can be fixed, variable or semivariable

To reduce overall costs and increase revenue from this operation, one common methodology used in decision making is an optimization model (Muñoz-Villamizar, Santos, Montoya-Torres, & Jaca, 2018)

Total Productive Maintenance (TPM)

TPM is a concept that aims to improve production performance by maintaining equipment. TPM has been developed by Japan since 1960 and 1970, which is based on the concept of Preventive Maintenance and Productive Maintenance or commonly abbreviated as PM developed in the United States (King, 2009).

The 4 stages of TPM development include (Nakajima, 1988):

- Breakdown Maintenance
- Preventive Maintenance
- Predictive Maintenance
- TPM (Total Productive Maintenance)

(Gupta, P., & Vardhan, S.,2016)Increased sales volume can be obtained by improving performance equipment, increase plant productivity, and reduce production costs through total productive maintenance (TPM)

OEE measurement (Overall Equipment Effectiveness) is a measurement of the performance of a machine, which is influenced by the value of three factors, namely Availability, Performance efficiency and Quality (Singh Rajput, H., & Jayaswal, P. (2012).

In the current era of the modern manufacturing industry where machines as the driving force of business and technology become a corporate strategy in the face of industrial market competition (Siregar, A. R., Purba, H. H., & Aisyah, S. (2017)

Six Big Losses

In every equipment performance, of course, there are losses that occur during operation, this is described into six big losses on equipment by Nakajima (1988), including:

- **Downtime Losses**
- Equipment Failure (Breakdown)

Equipment Failure is damage to equipment consisting of two types, namely sporadic failure and chronic failure. Sporadic failure is a sudden engine failure, usually this damage can be identified and repaired. Conversely, chronic failure is a type of minor damage to equipment, but when damage occurs, we cannot clearly identify the cause and the resulting impact is insignificant.

- Set up and Adjustment Losses

This is the time used to install, adjust and adjust the engine parameters to get the desired specifications when first starting to produce certain components / products.

In addition, Garvin (1988) offers eight product quality dimensions as defined from the customer's perspective: performance, features, reliability, conformance, durability, marketing, aesthetics, and perceived quality.

- **Speed Losses**
- Idling and Minor Stoppages

Idling Losses occur when the equipment or machine stays on but does not produce output, such as delays in material supply, etc. While Minor Stopping Losses is a stop that occurs on the equipment in a short time due to temporary problems, such as a component malfunction, quality problems that occur during the process etc.

- Reduced Speed

Is a loss caused by the speed of equipment that is operated under a predetermined standard, this is caused by several factors such as mechanical problems, nonstandard raw material, setting the machine that is not according to procedures that make the speed of the machine or equipment decreases.

- **Quality Losses**
- Defect in Process

It is a waste of time to produce a bad product and rework when the machine is running continuously after adjusting and adjusting the equipment.

- Reduced Yield

This loss is a loss caused by a product that is not in accordance with the standard. So that the reduced number of outputs is appropriate for the quality of the product.

With the elimination of the Six Big Losses can help to improve Equipment performance (OEE) and increasing the productivity (Ariyanto, D., 2017).

Partial Least Square – Structural Equation Modelling

Structural Equation Modelling (SEM) is a multivariate data analysis method used in this study and can be used as a data source (Statsoft, 2013). SEM can also be used in solving problems for latent variables that cannot be calculated and difficult to measure (Wong, 2013).

There are two approaches to SEM: The first approach is the widely applied covariance- based SEM (CB-SEM). CB-SEM has been widely applied in the field of social science during the past several decades, and is still the preferred data analysis method today for confirming or rejecting theories through testing of hypothesis, particularly when the sample size is large, the data is normally distributed, and most importantly, the model is correctly specified. That is, the appropriate variables are chosen and linked together in the process of converting a theory into a structural equation model (Hair et. al.., 2011).

PLS handle all types of data, from nonmetric to metric, with very minimal assumptions about the characteristics of the data (Hair et. al., 2010). Also, it handles both reflective and formative constructs and all recursive models are identified. However, many industry practitioners and researchers note that, in reality, it is often difficult to find a data set that meets these requirements. Furthermore, the research objective may be explored, in which we know little about the relationships that exist among the variables. In this case, researchers can consider PLS.

The second approach is Partial Least Squares (PLS), which focuses on the analysis of variance and can be carried out using PLS-Graph, Visual PLS, Smart PLS, and Warp PLS. PLS is a soft modelling approach to SEM with no assumptions about data distribution. Thus, PLS-SEM becomes a good alternative to CB-SEM when the following situations are encountered (Wong, 2010):

- Sample size is small.
- Applications have little available theory.
- Predictive accuracy is paramount.
- Correct model specification cannot be ensured.
- Definition of Normal Distribution is free.

It is important to note that PLS-SEM is not appropriate for all kinds of statistical analysis. Researchers also need to be aware of some weaknesses of PLS-SEM, including:

- High-valued structural path coefficients are needed if the sample size is small.
- The problem of multi collinearity if not handled well.
- Since arrows are always single headed, it cannot model undirected correlation.
- A potential lack of complete consistency in scores on latent variables may result in biased component estimation, loadings and path coefficients.
- It may create large mean square errors in the estimation of path coefficient loading.

In spite of these limitations, PLS is useful for structural equation modelling including formative indicators in applied research projects, especially when there are limited participants and that the data distribution is skewed, e. g., surveying female senior executive or multinational CEOs (Wong, 2011). PLS-SEM has been deployed in many fields, such as behaviour sciences, marketing, organization, management information system, and business strategy.

METHODOLOGY

Based on the literature review presented, a research model is proposed where 3 OEE (X1) variables are Availability (L12) indicators, performance indicators (L34) and Quality (L56) indicators. These three indicators are composed of Six Big Losses, namely: Equipment Failure (Breakdown), Setup Losses and Adjustments, Minor Stopless, Reduce Speed, Defect in the process and Reduce Yield that affect productivity (Y1) with Production Volume (Q1) and Yield production (Q2), decreased production / cost (Y2) costs with indicators (C1.1 - C1.7 and C2.1 - C2.6) and company profitability performance (Y3) with sales volume (Q3) and profit indicators (Q4) shown in figure 2.

The research hypothesis determines that there are important factors that influence the operational effectiveness of production, namely productivity, which will affect the parameters of each cost item and the company's profitability performance. In that view, the research hypothesis is as follows:

- **H1:** OEE will have a positive effect on factory productivity performance.
- **H2:** Productivity will have a positive effect to reduce costs.
- **H3:** Lower total costs will have a positive impact on the company's profitability performance

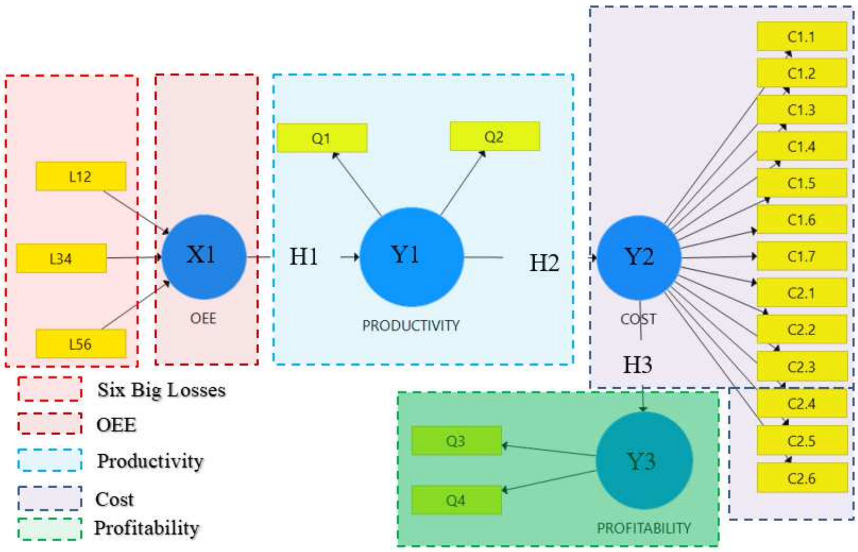

Figure 2: Research Model

Data is collected from the operational performance of the steel rolling mill company PT. XYZ for 3 years 2015 - 2017 will be examined using SmartPLS 3.0 to evaluate the reliability and validity of the research model and also to assess the research hypothesis.

RESULTS

Evaluation of Measurement Reflective Model (Outer Model)

- Internal Consistency Reliability, has been fulfilled with value*Composite Reliability (CR)*> 0,7 according to Table 1

Table 1: Composite Realibility

Variable Manifest	CR	AVE
Cost	0.997	0.960
Productivity	0.993	0.986
Profitability	0.997	0.994

- Indicator Reliability, has been fulfilled according to Table 2 with a valueof outer *loading*> 0.7

Table 2: Indicator Reliability

Indicator	Outer Loading	Explanation
C1.1	0.999	> 0.7
C1.2	0.995	> 0.7
C1.3	0.996	> 0.7
C1.4	0.996	> 0.7
C1.5	0.996	> 0.7
C1.6	0.951	> 0.7
C1.7	0.999	> 0.7
C2.1	0.997	> 0.7
C2.2	0.994	> 0.7
C2.3	0.959	> 0.7
C2.4	0.998	> 0.7
C2.5	0.997	> 0.7
C2.6	0.847	> 0.7
Q1	0.993	> 0.7
Q2	0.993	> 0.7
Q3	0.997	> 0.7
Q4	0.997	> 0.7

- Convergent Validity, has been fulfilled according to Table 1with value of AVE > 0,5
- Discriminant Validity, Based on the data presented in Table 3, it is known that Fornell-Larcker Criterioneach indicator in the research variable has the greatest value on the variables it forms compared to the values on other variables.

Table 3: Fornell-Larcker Criterion

Variable Manifest	Cost	Productivity	Profitability
Cost	0.980		
Productivity	-0.948	0.993	
Profitability	-0.985	0.939	0.997

Evaluation of Measurement Formative Model (Outer Model)

- Convergent Validity, has been fulfilled based on Table 4 R-square value between 0.64 - 0.81

Table 4: R-Square

Variable Manifest	R-Square	Explanation
Cost	0.898	> 0.64
Productivity	0.984	> 0.64
Profitability	0.970	> 0.64

- Collinearity Issue, has been fulfilled based on Table 5 values of VIF <5

Table 5: Outer VIF

Indicator	VIF	Explanation
L12	1.360	< 5
L34	1.077	< 5
L56	1.278	< 5

- Significance and relevance of the formative indicators, has been fulfilled based on Table 6 the value of P-value outer weight> 0.05

Table 6: P-Value Outer Weight

Indicator	Outer Weight	Explanation	Outer Loading
L12	0.888	> 0.5	0.71
L34	0.726	> 0.5	0.507
L56	0.003	> 0.5	0.393

Evaluation of Structural Measurement (Inner Model)

- Collinearity Assessment, has been fulfilled based on Table 7VIF inner model value <5

Table 7: VIF Inner Model

Variable	Cost	Productivity	Profitability
Cost			1.00
OEE		1.00	
Productivity	1.00		

- Structural Path Coefficient Model, based on Figure 3 and Table 8 the value of the T-statistic of all variables is greater than 1.96 and the value of P-value <α (0.05) so that we can say that the inner model is very significant.

Table 8: Coefficient and Effect Evaluation of Structural Model

Effect	Standard Dev	T Statistics	P Values
Cost -> Profitability	0.007	133.402	0.000
OEE -> Productivity	0.003	304.210	0.000
Productivity -> Cost	0.027	34.556	0.000

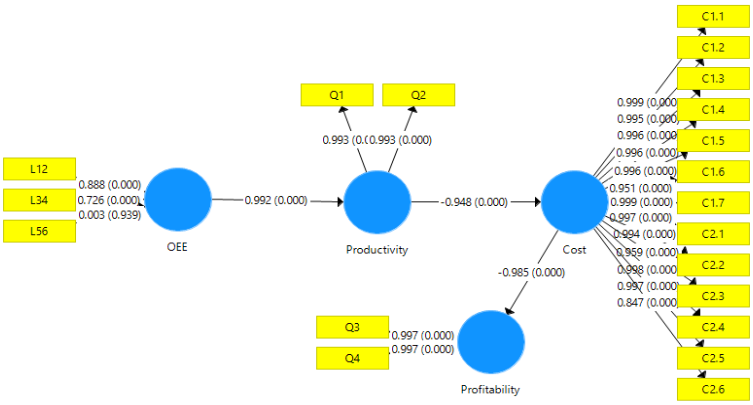

Figure 3: Result of Structural Model

- Coefficient of Determination, based on Table 9, the R^2 value of 0.75 is considered to have a large prediction accuracy.

Table 9: Determination Coefficient

Variable Manifest	R-Square
Cost	0.898
Productivity	0.984
Profitability	0.970

Based on R^2 values in Table 9 above, it can be seen that the value of R^2 for the construct variable Cost is 0.898, the value explains that the magnitude of the Cost can be explained by its indicators(fix and variable costs) of 89.8%. Then for the value of R^2 obtained by the productivity construct of 0.984, the value explains that the magnitude of the effect of productivity can be explained by the indicators of production volume and yield of 98.4%. And for the value of R^2 obtained profitability construct of 0.97, this value explains that the amount of profitability can be explained by profit and sales of 97.0%.

- Effect Size, Based on f^2 value in table 10 it can be seen that the Cost to Profitability and OEE to Productivity has a large effect size. Whereas Productivity to Cost has a small effect size

Table 10: Effect Size

Variable Manifest	Cost	Productivity	Profitability
Cost			0.326
OEE		0.600	
Productivity	0.088		

- Predictive Relevance, Q^2 value is obtained by using a blindfolding procedure to evaluate the value of ^{R2} as a criterion of prediction accuracy where, according to table 11, a value above 0.35 has a large predictive relevance. So that the predictive relevance for the variable Cost, Productivity and Profitability is large.

Table 11: Predictive Relevant

Variabel	Q^2
Cost	0.874
Productivity	0.626
Profitability	0.654

CONCLUSIONS

Three (3) hypotheses proposed : OEE to Productivity (H1), Productivity to Cost (H2) and Cost to Profitability (H3) in this study, all can be accepted because each of them gives a significant positive effect which is shown to have a P-Values value <0.05

Variable and fixed costs can be reduced by increasing productivity with reducing down time losses caused by engine damage and increasing the performance or speed of the production process.

To increase the profitability of steel rolling mills PT. XYZ, the priority improvements that must be made to eliminate six big losses are to improve four (4) indicators of Availability (L12) and Performance (L34) variables, namely elimination Breakdown losses (L1), Setup and Adjustment losses (L2), Idling and Minor Stoppages (L3), and Reduced speed (L4).

REFERENCES

1. *Ariyanto, D. (2017). Optimalisasi Kinerja Mesin Dengan Pengukuran Overall Equipment Effectiveness (OEE) Dan Minimalisasi Six Big Losses Pada Mesin Printing Sungan 2. International Journal.*
2. *Gupta, P., & Vardhan, S. (2016). Optimizing OEE, productivity and production cost for improving sales volume in an automobile industry through TPM: A case study. International Journal of Production Research, 54(10), 2976–2988. https://doi.org/10.1080/00207543.2016.1145817*
3. *Hair et al. (2014). 8. Josephb F. Hair, G. Tomas M. Hult, Christian M. Ringle, Marko Sarstedt-A Primer on Partial Least Squares Structural Equ (2014th ed.). https://doi.org/10.1016/j.lrp.2013.01.002*
4. *Hasni. (2011). Peranan Sektor Baja Dalam Perekonomian Indonesia (Vol. Vol. 5 No.). Buletin Ilmiah Litbang Perdagangan*
5. *Heyzer. J., R. B. (2001). Operations Management.*
6. *King, P. L. (2009). (2009). Lean For The Process Industries: Dealing With Complexity. New York: Taylor & Francis group.*
7. *George, J. P., & Pramod, V. R. (2014). An interpretive structural model (ISM) analysis approach in steel re rolling mills (SRRMS). International Journal of Research in Engineering & Technology (IMPACT: IJRET), 2(4), 161-174.*
8. *Maletič, D., Maletič, M., Al-Najjar, B., & Gomiščček, B. (2012). The role of maintenance regarding improving product quality and company's profitability: A case study. IFAC Proceedings Volumes (IFAC-PapersOnline), 45(31), 7–12. https://doi.org/10.3182/20121122-2-ES-4026.00040*
9. *Dae-Sung, K., Ji-Hyeung, Y., & Hong-Duk, M. (2016). Non-Destructive Stress Measurement of Civil Structural Steel Using Magnetic Anisotropy Sensor.*
10. *Muñoz-Villamizar, A., Santos, J., Montoya-Torres, J. R., & Jaca, C. (2018). Using OEE to evaluate the effectiveness of urban freight transportation systems: A case study. International Journal of Production Economics, 197, 232–242. https://doi.org/10.1016/j.ijpe.2018.01.011*

11. *Nakajima, S. (1988). Introduction to TPM (Total Productive Maintenance). Productivity Press, Inc*

12. *P. Tampubolon, M. (2004). Manajemen Operasional (operations Management). Ghalia Indonesia.*

13. *Prasetyo, P. (2010). Struktur dan Kinerja Industri Besi dan Baja Indonesia tidak sekuat dan sekokoh namanya. JEJAK Volume*

14. *Singgih, S. (2006). Menguasai Statistik Di Era Informasi Dengan SPSS 15. Jakarta: Elex Media Komputindo.*

15. *Singh Rajput, H., & Jayaswal, P. (2012). A Total Productive Maintenance (TPM) Approach To Improve Overall Equipment. International Journal of Modern Engineering Research, 2(6), 4383–4386. https://doi.org/10.1109/WICSA-ECSA.212.31*

16. *El-Shennawy, M., Farahat, A. I., Masoud, M. I., & Abdel-Aziz, A. I. (2016). Effect of Boron Content on Metallurgical And Mechanical Characteristics of Low Carbon Steel. Int. Jl. Mech. Engg.(IJME), 5(2), 1-14.*

17. *Siregar, A. R., Purba, H. H., & Aisyah, S. (2017). Measuring Overall Equipment Effectiveness (Oee) Palm Oil Mill in Indonesia. International Journal of Recent Trends in Engineering and Research, 3(12), 164–170. https://doi.org/10.23883/IJRTER.2017.3551.ZQ21L*

18. *Wong, K. K. K.-K. (2013). 28/05 - Partial Least Squares Structural Equation Modeling (PLS-SEM) Techniques Using SmartPLS. Marketing Bulletin, 24(1), 1–32. https://doi.org/10.1108/EBR-10-2013-0128*

19. *Worldsteel. (2016). Steel Statistical Yearbook 2016. WorldSteel Association,*

https://doi.org/http://www.worldsteel.org/statistics/statistics-archive/yearbook-archive.html